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Contrast Optimization by Metaheuristic for Inclusion Detection in Nonlinear Ultrasound Imaging

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Abstract

In ultrasound imaging, improvements have been made possible by taking into account the harmonic frequencies. However, the transmitted signal often consists of providing empirically pre-set transmit frequencies, even if the medium to be explored should be taken into account during the optimization process. To resolve this waveform optimization, transmission of stochastic sequences were proposed combined with a genetic algorithm. A medium with an inclusion was compared in term of contrast to a reference medium without defect. Two media were distinguished thanks an Euclidean distance. In simulation, the optimal distance could be multiplied by 4 in comparison with an usual excitation.

Keywords: Inclusion detection, Metaheuristic, Optimal command, ultrasound

1. Introduction

Medical ultrasound imaging has become an essential tool for clinical diagnosis over the past fifty years. Historically, its principle is simple. An ultrasound sinus wave of frequency f_0 is transmitted into the medium being explored. Acoustic impedance changes due to medium changes generate echoes which make possible the image reconstruction. However developments of harmonic imaging techniques have brought about a revolution. Actually, the ultrasound wave nonlinearly propagates through the tissue under exploration. Consequently, harmonic components ($2f_0, 3f_0, \dots$) are generated and they are measured in the echoes. By extracting each harmonic component, it is possible to obtain harmonic images with high contrast [1]. However, the axial resolution can be limited, because good separation of the harmonic components requires a limited pulse bandwidth [2]. Several imaging methods have been proposed to improve contrast while ensuring a good axial resolution, such as pulse inversion imaging [3]. Since the most commonly used is the pulse inversion imaging, we only focused our study with this technique.

However, to optimally use the pulse inversion imaging, the transmitted pulse must be correctly adjusted. Nevertheless conventional ultrasound scanners can only provide some transmit frequencies for manual selection to construct a transmitted signal at this fixed frequency. In previous studies, we were able to optimize the contrast of the image by seeking the transmitted signal. The first solution carries on transforming the shape optimization in a suboptimal parametric optimization [5]. The automatic tuning of transmit frequency made possible the maximization of the contrast. To overcome the suboptimal solution, the second method has been enabled to extend this principle without assumption on the waveform. This approach is based on the transmission of stochastic waves [6].

The aim of the study was to find automatically the optimal command which can distinguish two different tissues in a medium; for example an inclusion. We proposed to compare this medium with a reference medium without flaw

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in order to construct a distance between them. If the distance is maximal, the flaw must be more visible, since it is the only difference between the two media. We therefore replaced the current pulse inversion system with a closed loop system whose transmitted pulse w was modified by feedback. We propose to solve the shape optimization by using a genetic algorithm and we applied it in simulation. The advantage of the method was the optimization without *a priori* knowledge on the optimal waveform and on the medium.

2. Closed Loop System

The principle of our pulse inversion imaging includes feedback. For an individual solution at the iteration k , two pulses $x_{k,1}(n)$ and $x_{k,2}(n)$ with opposite phase were transmitted into the medium with a flaw or an inclusion and into the reference medium without flaw. For each medium m , the sum $z_{m,k}(n)$ of their two respective echoes $y_{m,1,k}(n)$ and $y_{m,2,k}(n)$ enabled to extract the even harmonic components [3] and it formed a radiofrequency (RF) line $l_{k,m}$. From these two RF lines $l_{k,1}$ and $l_{k,2}$, the distance d_k was computed. Finally, a new transmitted binary signal $x_{k+1,1}$ was computed by the algorithm to optimize the distance d_{k+1} .

2.1. Transmitted Stochastic Signal

The stochastic pulse signal $x_{k,q}$ in pulse inversion imaging was digitally computed with Matlab (Mathworks, Natick, MA, USA):

$$x_{k,q} = (-1)^q \cdot A \cdot w_k(n). \quad (1)$$

The number of samples N_s was set so that the duration T of the stochastic signal $w_k(n)$ corresponded to 100% of the fractional bandwidth of the transducer. Their values should be thus selected for optimization. Finally, the amplitude of the driving pressure A was then adjusted so that the power of the pulse $x_{k,q}(n)$ was constant to the $P_{x_{ref}}$ of the impulse response of the transducer with a driving pressure A_0 .

2.2. Cost Function

The cost-function to be maximized was an Euclidean distance between the two media: the medium with flaw and the reference medium. Since the acoustic propagation into the medium was nonlinear, the RF lines had harmonic components. To take into account this property, we proposed to split the transducer bandwidth within 4 sub-bands. Note that the number of sub-bands was slightly higher than the maximum number of harmonic components which could be observed. A power was thus computed for each sub-band and each environment. Finally, the Euclidean distance was defined from these powers as:

$$d_k = \sqrt{\sum_{i=1}^4 (E_i(l_{1,k}) - E_i(l_{2,k}))^2}, \quad (2)$$

where $(E_i(l_{1,k}))$ is the power backscattered for the medium with the flaw in the i -th sub-band and $E_i(l_{2,k})$ is the power backscattered for the reference medium in the i -th sub-band.

2.3. Algorithm

As previously explained, the search for the optimal command $w_k^*(n)$ was based on the selection of the optimal stochastic signal which maximized the cost function: $w_k^*(n) = \arg \max_{w_k} (d_k)$. This step was hard optimization problem. By using a genetic algorithm [7], it was possible to add an optimization process based on the genetic reproduction. The algorithm thus had the role of search N_s samples to maximize distance d . At the iteration k , 12 stochastic signals [7] were transmitted to the two media. Each sample was randomly chosen from a continuous uniform distribution between -1 and 1. For the generation $k + 1$, only the 6 best individual solutions which maximized the contrast were selected to become parents. It remained to construct 6 new solutions named offspring. To construct them, the crossover operator mixed the best parent with one of the 5 remaining parents. Finally, 40% samples were mutated to obtain robust optimization. Thus the optimal stochastic command was the best individual solution of generation k .

3. Simulation Model

The simulation model was constructed on the basis of the pulse inversion imaging system to contrast realistic ultrasound image which have already proven in medical ultrasound imaging [5]. It was composed of different phases: transmission, 2D nonlinear propagation and reception.

At the transmitter, a stochastic signal $x_{k,1}(n)$ was generated digitally and filtered by the transfer function of a realistic transducer, centred at $f_c = 4$ MHz with a fractional bandwidth of 75% at -3 dB. The pulse wave generated was propagated nonlinearly into each attenuating medium [4]. In the first medium, a 5 mm-diameter inclusion of a second tissue was inserted into the first tissue at 12 mm below the surface, whereas in the second medium, no inclusion was added (Fig. 1 (left)). Finally, the signals backscattered by tissue were recorded for each medium. These tissue echoes were filtered by the transfer function of the transducer to construct the first echoes. The simulation process was repeated with the second transmitted stochastic pulse $x_{k,2}(n)$ to construct the second echoes. Then the envelope of the RF line $l_{k,m}$ was calculated allowing the determination of the distance d_k .

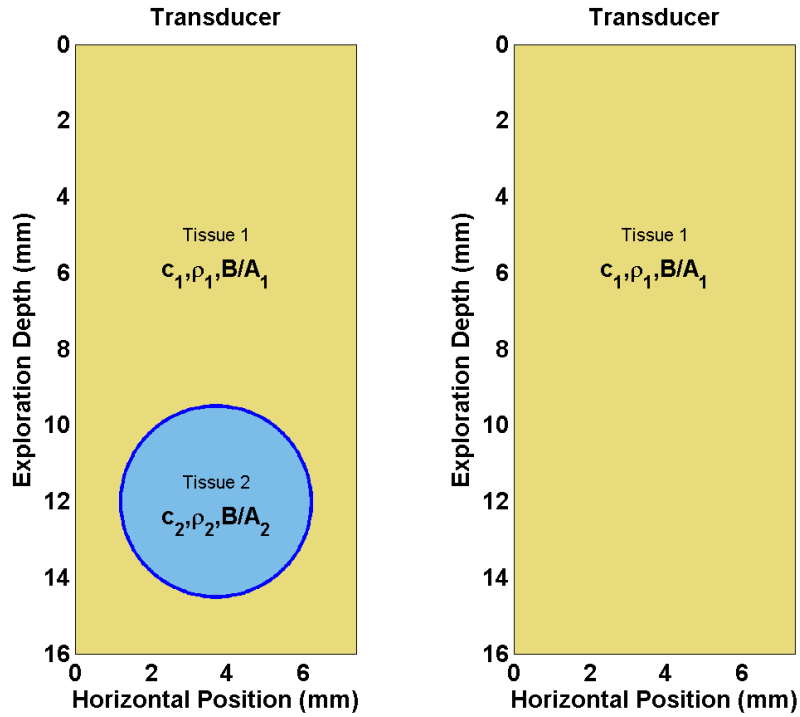


Figure 1: (Left) Grid of properties of the medium with the inclusion and of the reference medium without inclusion: c is the wave velocity, ρ the density and B/A the nonlinearity parameter. The ultrasound transducer was at a depth of 0 mm, here at the top. (Right) Simulation of automatic optimization of the distance d_k by a transmitted stochastic signal. The optimization was compared with the case where the transmitted signal is at the central frequency f_c of the transducer, *i.e.* the usual transmitted signal used in tissue harmonic imaging.

4. Results

The optimization process was applied in the simulation model to demonstrate the feasibility of our novel method. The driving pressure A_0 was set to 400 kPa. The duration T of the binary signal represented 100% of the fractional bandwidth of the transducer. The sample number was thus 40 according to the sampling rate required to the simulation model.

Fig.1(right) shows the best Euclidean distance as a function of generation k . As an illustration, this result was compared with the usual transmitted signal used in tissue harmonic imaging, *i.e.* with a transmit frequency at the

central frequency f_c of the transducer. After 3000 generations, the Euclidean distance d_k reached an optimal value four times superior than with usual excitation at the central frequency of the transducer. Note that it was also possible to double the distance with less than 50 generations.

Fig.2a shows the optimal stochastic command $w_k^*(n)$. As an illustration, Fig.2b shows the signal $p(n)$ at the transducer output when $w(n)$ was the optimal stochastic signal. This signal was transmitted in tissue. Fig.2c shows the respective radiofrequency lines for the medium with the flaw and the spectra of input/output imaging system in Fig.2d. Note that in contrast with the usual transmitted signal, the optimal transmitted signal had nonlinear components. In order to illustrate the improvement on the ultrasound images, Fig.2e and f show the synthetic images using the usual transmitted signal at the central frequency of the transducer f_c and the optimal stochastic signal. For a distance of four obtained with 3000 generations, the images show a high increase in the contrast between the two tissues by using the optimal stochastic command.

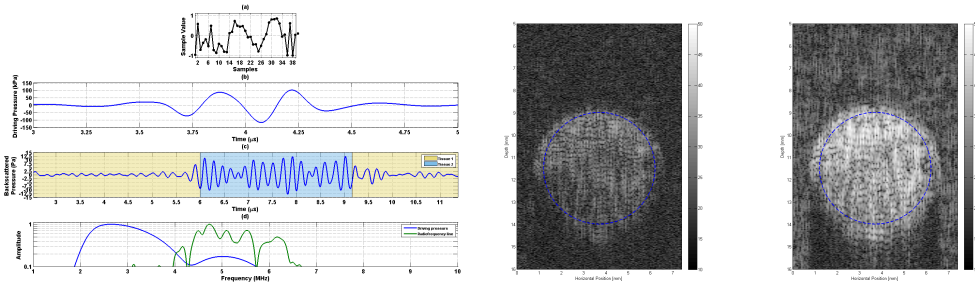


Figure 2: (a) Optimal transmitted stochastic signal $x_{k,1}(n)$ obtained by the genetic algorithm. (b) Signal $p(n)$ at the transducer output when $w(n)$ was the optimal stochastic signal. (c) Corresponding radiofrequency line measured with the medium with the flaw. (d) The respective spectra. (e) Synthetic Images using the usual transmitted signal at the central frequency of the transducer f_c , and (f) the optimal stochastic signal.

5. Discussion and Conclusion

Stochastic sequences were automatically transmitted through a pulse inversion imaging system in order to optimize an Euclidean distance frame by frame. The closed loop system automatically provided an optimal stochastic command where the Euclidean distance was higher than with a fixed-frequency transmitted signal. This optimization was performed without taking into account a priori knowledge of the medium and the transducer. This performance lied in the definition of the function of cost. By comparing it with a reference medium, the optimization was highlighted flaws over the surrounding tissue. If a reference medium is no more required, a procedure of delineation/segmentation can be performed to extract a reference region without flaw.

In conclusion, this method improved the quality of images without assumptions on the waveform or on the position of the inclusion / flaw. This new paradigm seems to be suitable for non destructive testing.

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